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BRAIN LESION SEGMENTATION USING FUZZY C-MEANS ON DIFFUSION-WEIGHTED IMAGING

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ABSTRACT

This paper presents an automatic segmentation of brain lesions from diffusion-weighted imaging (DWI) using Fuzzy C-Means (FCM) algorithm. The lesions are acute stroke, tumour and chronic stroke. Pre-processing is applied to the DWI for intensity normalization, background removal and enhancement. After that, FCM is used for the segmentation process. FCM is an iterative process, where the process will stop when the maximum number of iterations is reached or the iteration is repeated until a set point known as the threshold is reached. The FCM provides good segmentation result in hyperintensity and hypointensity lesions according to the high value of the area overlap, and low value of false positive and false negative rates. The average dice indices are 0.73 (acute stroke), 0.68 (tumour) and 0.82 (chronic stroke).

Keywords: diffusion-weighted imaging, brain lesion, fuzzy c-means.

INTRODUCTION

Magnetic Resonance Imaging (MRI) is one of the popular, painless, non-radiation and non-invasive brain imaging techniques (Holdsworth and Bammer, 2008). MRI produces images of high spatial resolution (mm) with excellent soft tissue contrast that has made it useful for detecting brain tissue abnormalities (Krishnan et al., 2004). Diffusion-weighted imaging (DWI) is increasingly playing an important role in diagnosis of brain lesions. Due to its ability to provide image contrast that is dependent on the molecular motion of water. Diffusion of water molecules in pure water occurs randomly, but does not occur in the cellular environment as it is restricted by cellular boundaries and macromolecules. The diffusion properties of water molecules can be measured using DWI (Gray and MacFall, 1998). DWI also provides additional information about diseases such as neoplasms, intracranial infections and others. The acquisition is noninvasive and does not require any contrast agent. Thus, it can be established a routine patient evaluation.

Automatic segmentation can extract boundaries from a large number of images with a little time and effort. The segmentation algorithm is based on the properties of grey level values of pixels (EvelinSuji, V. S. Lakshimi and Wiselin Jiji, 2013). Image segmentation methods can be categorized into three categories: edge-based methods, region-based methods, and pixel-based methods; both supervised and unsupervised. Unsupervised segmentations are fully automatic and the regions are partitioned in feature space with high density. Feature-space based techniques, clustering and adaptive thresholding are examples of unsupervised algorithm (Jobin and Parvathi, 2011). In region-growing segmentation the regions are based on intensity information or edges in the image (Saad et al., 2012). An operator manually chooses a seed point and extracts all the pixels connected to the initial seed based on some predefined criteria. Region growing can be sensitive to noise, causing extracted regions to have holes or to be disconnected. The split and merge technique is known as quad-tree segmentation, which is based on a quad-tree partition of an image. However, it is not a pixel based segmentation (Saad et al., 2010).

Clustering is the process of forming objects into groups whose members have similar characteristics. Three commonly used clustering algorithms are k-means, fuzzy c-means (FCM), and expectation-maximization (EM) algorithms. Every method has its advantages and disadvantages. The weakness of FCM is its sensitive to noise and that it only considers clustering based on intensity. EM performs the segmentation as a normal Gaussian distribution, but generally, a noisy image is not a normal distribution (Ahirwar, 2013), (Dokur, 2008), (M.A et al., 2008). A modified FCM algorithm is used to overcome the problem by incorporating the spatial neighborhood information into the standard FCM algorithm and modifying the membership weighting of each cluster (Anangaonkar, 2013).

This paper discusses automatic segmentation of brain lesions from DWI using a Fuzzy C-Means approach. This paper is organized as follows. The proposed techniques are discussed in details in section II. The section starts with flowchart of the proposed method first, followed by the DWI used for this paper and a description of the segmentation process. In section III, experimental results of applying the algorithm are applied. The conclusion is discussed in section IV.

RESEARCH METHODLOGY

Fuzzy C-means algorithm

Fuzzy C-Means (FCM) is an iterative process that allows data that belong to two or more clusters with

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different membership coefficients. The initial fuzzy partition matrix is generated and then the initial fuzzy cluster centers are calculated. The cluster centers and the membership grade point in each step of the iteration are updated, and the objective function is minimized to find the best position for the clusters. The process stops when the maximum numbers of iterations is reached, or when the objective function improvement between two consecutive iterations is less than the minimum amount of improvement specified. The iteration of FCM is performed through two parameters, namely the membership degree and the center of the cluster. These parameters changed when the repeated steps stop at a threshold or stop when the maximum number of iterations is reached. Besides, the changes of these parameters are influenced when the objective function improvements of two consecutive iterations are less than the minimum amount of improvement specified (Tirpude and Welekar, 2013). Figure-1 depicts the flowchart of the FCM segmentation.

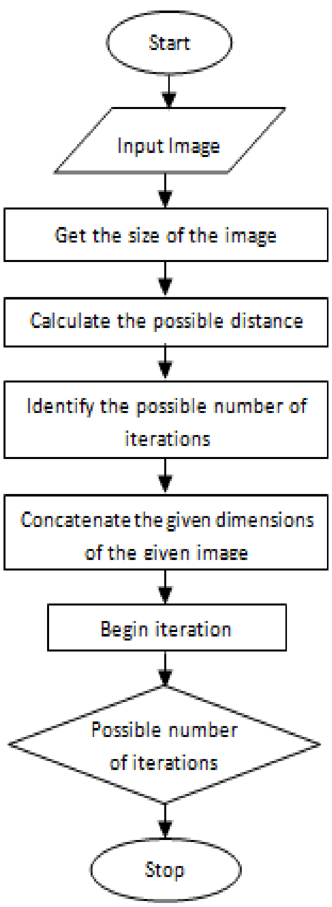

Figure-1. Flowchart of FCM Segmentation

The algorithm consists of the following steps:

1) Read the image into the MATLAB.
2) Identify the number of iterations within a given period of time.
3) Get the size of the image.
4) Calculate the possible distance using repeating structure.
5) Concatenate the given dimension of the image size.
6) Repeat the matrix to generate large data items in carrying out the possible distance calculation.
7) Begin iterations by identifying large component of data vis-a-vis the value of the pixel.
8) Stop iteration when possible identification elapses.

Generate the time taken to segment.

Diffusion-weighted MRI sample

The DWI has been acquired from General Hospital of Kuala Lumpur using 1.5T MRI scanners Siemens Magnetom Avanto. The acquisition parameters used were time echo (TE), 94ms; time repetition (TR), 3200 ms; pixel resolutions, 256x256; slice thickness, 5 mm; gap between each slice, 6.5 mm; intensity of diffusion weighting known as b value, 1000 s/mm^2 and total number of slices, 19. All samples have medical records which have been confirmed by neuroradiologists. Images were encoded in 12-bit DICOM (Digital Imaging and Communications in Medicine) format. The proposed method has been tested on a dataset of 20 MRI brain images with various types of lesions.

Fuzzy C-means segmentation process

FCM is also known as a data clustering method in which each data point belongs to a cluster to a degree specified by a membership value. FCM divides a collection of n vectors into c fuzzy groups and finds a cluster centre in each group. FCM uses fuzzy partitioning such that a given data point can belong to several groups with the degree of belongings specified by membership values between 0 and 1. The Fuzzy C-Means algorithm applied in this study is summarized as follows:

1) Initialize the membership matrix U with random values between 0 and 1.
2) Calculate c fuzzy cluster center C_i, i = 1,2,..., c, using equation:

$$C_i = \frac{\sum_{j=1}^{n} u_{ij}^m x_j}{\sum_{j=1}^{n} u_{ij}^m} \quad (1)$$

3) Compute the cost by using the following equation. Stop if it is below a certain threshold value or its improvement over previous iteration is minimal:

$$J(U, C_1, ..., C_c = \sum_{i=1}^{c} \sum_{i}^{n} u_{ij}^m d_{ij}^2 \quad (2)$$

4) Compute new U by the equation. Go to step-2:

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$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{d_{ij}}{d_{kj}} \right)^{2/(m-1)}} \qquad (3)$$

A modified FCM algorithm (mFCM) for brain segmentation can be used to solve the noise problem in the FCM (Hussain et al., 2012), (Ibrahim et al., 2010). The algorithm is performed by incorporating the spatial neighbourhood information into the standard FCM algorithm and modifying the membership weighting of each cluster. These algorithms are useful to the artificial synthesized image and real image (Wang and Wang, 2008). Image segmentation determines the quality of the final results. Image segmentation divides an image into a number of non-overlapping regions where each region has distinct properties. The FCM clustering algorithm is an unsupervised clustering technique. When comparing this algorithm with the hard c-mean algorithm FCM preserves more information from the original image. The pixels on an image are highly correlated or, in other words, the pixels in the immediate neighbourhood have nearly the same feature data. Therefore, the spatial relationship of neighbouring pixels is an important parameter in imaging segmentation.

3-class fuzzy c-means clustering is being used for the fuzzy c-means algorithm. The command [bw,level]=fcmthresh(IM, sw) will give the output of a binary image (bw) and the threshold level of the image (IM). The sw values indicate the switch for the cut-off position, either 0 or 1. If sw=0, it refers to the cut between the small and middle class. If sw=1, this indicates that the cut is between the middle and large classes. Figure-2 illustrates the flowchart of FCM clustering in this study.

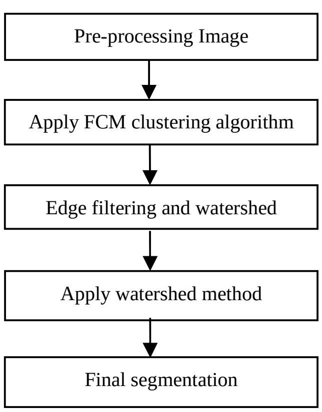

Figure-2. Flowchart of FCM Clustering in this study.

RESULT

Pre processing

A specific explanation about the pre-processing stage can be found in (Saad, Muda and Mokji, 2011).

Segmentation

Three clusters are used in this project low, median and high intensity clusters. The iteration is repeated until a set point called the threshold is reached. The process stops when the maximum number of iterations is reached. The FCM segmentation results are comparable with the manual reference segmentation, as shown in Figure-3. Due to the existence of noise, FCM does not consider the spatial information which makes it very sensitive to noise. Figure-3 portrays the image of DWI, manual reference and FCM results for accurate and inaccurate segmentations. The whole samples are included in the attached APPENDIX.

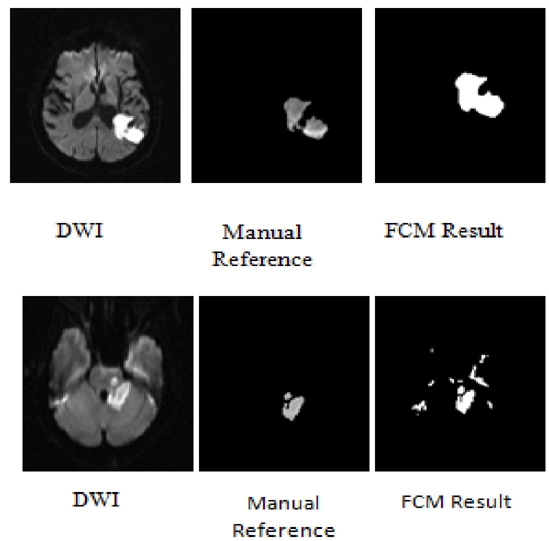

Figure-3. Result from DWI, manual reference and FCM.

Table-I depicts the performance evaluation for each lesion which are acute stroke, tumour and chronic stroke by using Fuzzy C-Means. The results portray the segmentation of chronic stroke provides very good segmentation results according to high AO with low FPR and low FNR. These lesions were successfully segment by using our proposed method due to their hypo intensity value properties.

Table-1. Performance evaluation of each lesion.

Index	Area Overlap (AO)	False positive rate (FPR)	False negative rate (FNR)	Dice
Acute stroke	0.6306	0.1572	0.2090	0.73
Tumour	0.5273	0.4120	0.1613	0.68
Chronic stroke	0.7077	0.0836	0.1322	0.82
Average	0.6219	0.2176	0.1675	0.74

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Table-2 shows the comparison results between fuzzy c-means, automatic region growing (Saad et al., 2012) and divergence measures of stoke regions (Bhanu Prakash et al., 2008). By comparing the performance of our proposed approach to other previous work on Table-II, our approach provides average performance results according to high AO and Dice Index; and low FPR and FNR. The proposed method can fully segment the lesions of DWI.

Table-2. Comparison between fuzzy C-means, and other techniques.

Index / Techniques	Area overlap (AO)	False positive rate (FPR)	False negative rate (FNR)	Dice index
Auto region growing	0.7089	0.0766	0.2145	n/a
Divergence measures (stroke region segmentation)	n/a	n/a	n/a	0.72
Fuzzy C-means	0.6219	0.2176	0.1675	0.74

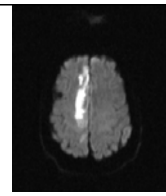
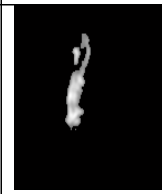
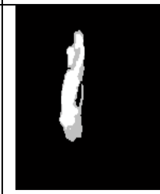
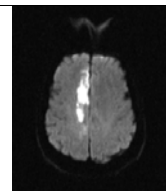
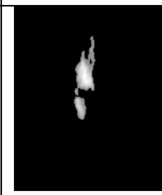
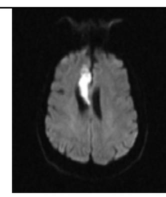
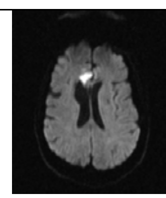
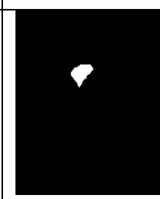
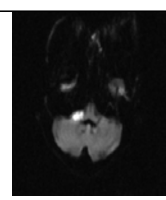
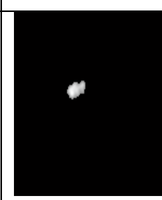
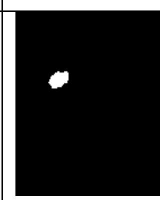
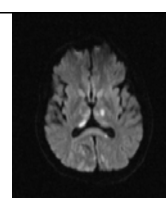
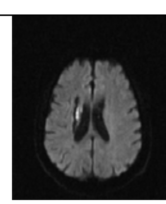
CONCLUSIONS

In this paper, the FCM algorithm has been implemented to segment the region of interest (ROI). This method is compared with the manual reference and other techniques to verify the accuracy. Based on the results, FCM provides good segmentation results in hyper intensity and hypo intense lesions according to the high value of area overlap and dice index, and low value of false positive and false negative rate. Average area overlap, false positive, false negative and dice index are 0.62, 0.22, 0.17 and 0.74 respectively.

APPENDIX

Table-3-5 show segmentation results for successful, noise appearance and unsuccessful segmentation. There are 20 samples which represent acute stroke, tumor and chronic stroke. Table-3 shows accurate lesion segmentation, where the lesions are hyper intensity and without noise. In Table-4, the segmentation includes hyper intensity signals generated by DWI. Table-5 shows the algorithm failed to segment the iso intense lesion.

Table-3. Accurate segmentation (successful segmentation).

No.	Original image	FCM results	Manual reference image
1			
2			
3			
4			
5			
6			
7			

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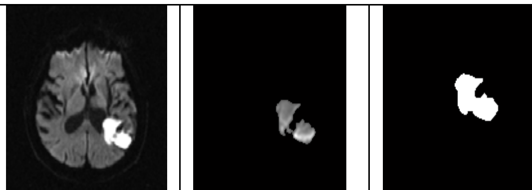
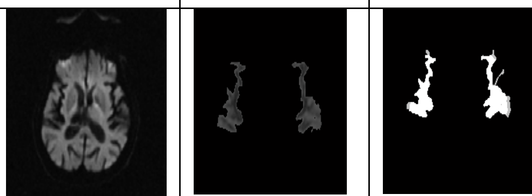
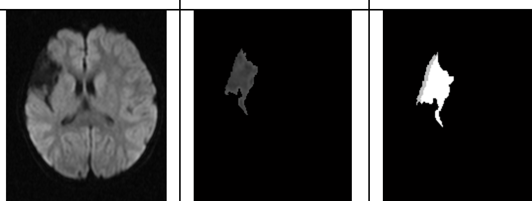
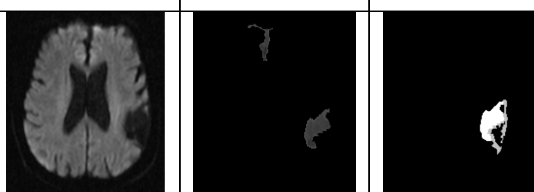
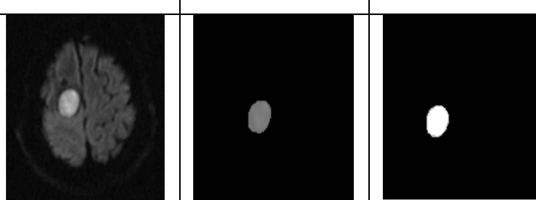
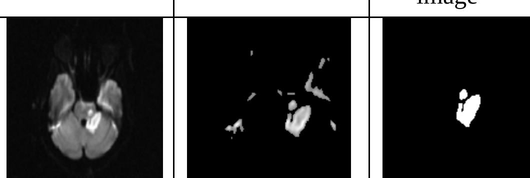
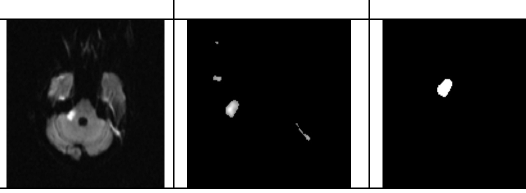
8			
9			
10			
11			
12			

Table-4. Image for segmentation with noise appearance (successful segmentation).

No.	Original image	FCM results	Manual reference image
1			
2			
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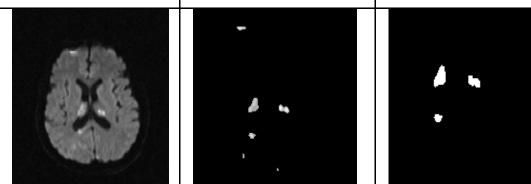
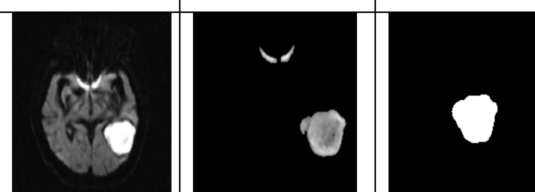
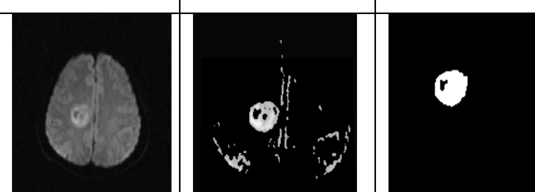
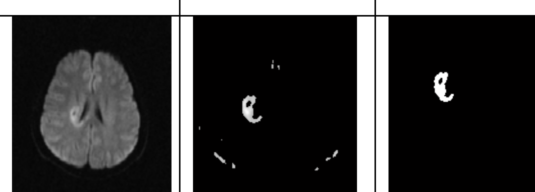
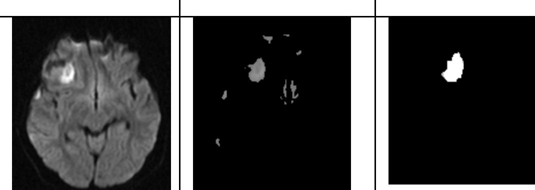
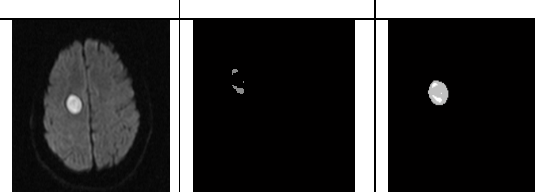
4			
5			
6			
7			
8			
9			
10			

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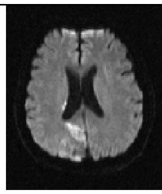
Table-5. Unsuccessful segmentation.

No.	Original image	FCM results	Manual reference image
23			

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